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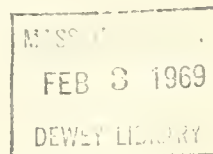
SPRINTER: A Model for the Analysis of New Frequently Purchased Consumer Products*

by

Glen L. Urban

ABSTRACT

This paper develops and demonstrates a model based information system to analyze a new frequently purchased consumer product and to serve as an adaptive control mechanism during national introduction. The model is based upon the behavioral process of the diffusion of innovation and can be used normatively in an iterative search mode to find the best marketing strategy for a new product. The input is obtained from test market data analyzed by statistics and combined with subjective judgment. A GO, ON, or NO decision is made on the basis of the estimated profit and risk produced by the best marketing strategy. During national introduction the model serves as a "problem finding" mechanism.[1] It uses early national sales and micro-level behavioral data to diagnose problems in the diffusion process. It also can be used to search for solutions to these problems as they are recognized. An application of this model to a real product and its testing are reported. This application uses an on-line computer program called SPRINTER: Mod III which allows effective man-system communication.[2]

[1] See [31].

[2] The first SPRINTER model is described in [38]. The original model was most useful for industrial or durable consumer products. SPRINTER: Mod II is is a simplified version of Mod III.

NEW PRODUCTS AND THE DIFFUSION OF INNOVATION

The pervasive nature of the new product decision and the high failure rate of new products makes this a fertile area for management science research. New products are a potential key to sales and profit growth, but they are also very risky since the innovative nature of a new product makes its acceptance difficult to predict. The key phenomenon is the diffusion of the new product innovation.[3] The mechanism is behavioral in nature and a model which aspires to be useful in the analysis of new products should be based on the behavioral science phenomena underlying the diffusion process. Models have been built to encompass the marketing strategy,[4] risk,[5] and information networking[6] and forecasting[7] aspects of new product decisions, but these models have not adequately modeled the basic diffusion and consumption process. Models have been developed at the behavioral level[8] and, although they have predictive capabilities, they have not demonstrated a capability to iteratively or algorithmically recommend the best decision among the many strategy alternatives available. This capability is necessary for a good analysis, model.

The purpose of this paper is to develop a normative behaviorally based model that is useful in the new product introduction decision. This represents an attempt to integrate behavioral science within a normative mathematical model to recommend strategies, specify the GO-ON-NO decision for the product, and adaptively guide a new product through national introduction.

The concept of diffusion of an innovation suggests that adoption of a new idea is not immediate and that some process accounts for the spread of the acceptance. The hypothesis is that a small segment of the population (called innovators) adopt an idea first. Then the idea spreads to others as the innovators pass information to them, as others observe the results of the innovator's acceptance, or as the others are exposed to mass media

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[3]See [33]; [4]See [38], [19]; [5]See [38],[9],[28]; [6]See [40],[8],[10]; [7]See [21], [6]; [8]See [1], [16].

communication and accept the idea without direct contact with an innovator. This hypothesis would lead to a distribution of people over the length of time before acceptance. This distribution has been found to be unimodel and symmetric for several successful agricultural innovations.[9] In the consumer field, some distributions have been found to be positively skewed.[10] These distributions have been rather arbitrarily divided into sections, each representing different adaptor classes. The most common divisions are: (1) innovators, (2) early adoptors, (3) early majority, (4) late majority, and (5) laggards. The phenomena underlying the diffusion of innovations have been studied by many behavioral scientists and a very large literature has developed. In spite of the volume of literature the number of conclusions and generalizations about the process are few.

Rogers and Stanfield have catalogued and studied this literature and have identified a number of emerging generalizations in the area.[11] They describe a set of generally accepted characteristics of innovators such as level of education, attitude towards change, cosmopoliteness, deviancy from norms, and exposure to interpersonal communications. These characteristics condition the structure of any new product decision, but of more particular interest are the properties of the innovation that encourage early adoption. The most significant factors identified by Rogers and Stanfield are relative advantage, compatability, and fulfillment of felt needs. These factors can be influenced by new product design, the product's price, and its communication strategy in terms of the appeals, media, and budget. The compatability of the new product to the adoptor will depend in part upon his perception of the social and psychological risks associated with the product.[12] This perception may be selective in nature.[13] Advertising may help in reducing the perceived risk of usage and overcoming selective perception biases. It also plays a role in reduc

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[9]See [33], pp. 160-165; [10]See [6]; [11]See [34]; [12]See [4],[12],[13],[30],[36]; [13]See [35].

the dissonance that can develop after the innovation has been tried and product use experience has been collected. This dissonance can result because the consumer is not sure he made a "good" purchase decision or because there is a difference between his expectations for the product and its actual performance. Such conditions are examples of cognitive dissonance..[14] Advertising may satisfy the desire to relieve this dissonance, if it exists, by reinforcing the correctness of the decision and emphasizing the good features of the product. In general, the post purchase processes of selective perception of use experience, selective forgetting of appeals, and word of mouth communication are important to recognize in examining the new product diffusion process.

Pessemier, Burget and Tigert have empirically identified some new product diffusion phenomena.[15] They found that innovators could be identified on the basis of observable characteristics, that they were active in more word of mouth transmission than non-innovators, and that they tended to be more trial prone than later adopters. The word of mouth communication flow between opinion leaders and other small group members appears to be an important phenomena in the diffusion process. The change of the trial proneness over the diffusion process is consistent with the diffusion structure that classifies consumers as innovators, early adopters, early majority, late majority, or laggards on the basis of their time of adoption.

The diffusion process describes the overall growth in acceptance, but it must be remembered that individuals make the decision to accept the innovation. Therefore the basic purchase decision process must be considered.[16] The development of awareness, attitudes, and preference must be specified. These should then be linked to higher functions such as the intent to purchase and search and finally to product selection. After purchase, the behavioral

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[14]See [14], [15], [5], [7]; [15]See [29]; [16]See [22].

processes of forgetting and interpersonal communication should be considered.

A behaviorally based model must explicitly include these diffusion of innovation phenomena within the basic purchase decision sequence and link the controllable new product variables to this process. Then alternate strategies can be evaluated and meaningful forecasts of sales and profits can be generated. These forecasts should be integrated with an evaluation of the risk, profit and investment to specify a GO-ON-NO decision for the product.

A NEW PRODUCT ANALYSIS INFORMATION SYSTEM

The construction of a behavioral process model requires the availability of good input data. This requirement is best satisfied by an information system to serve the new product decision. The system should contain a data bank of information relevant to the product, a bank of statistical programs to analyze and interpret the data, an input/output facility capable of communicating to managers,and the market response model. This paper will present such an information system for new frequently purchased consumer products. The heart of the system is a behavioral process model which is structured to consider the diffusion of innovation process of frequently purchased consumer goods and links the controllable variables to the process. The system data base is test market data and a set of flexible multivariate analysis routines will make up the statistical bank. The input/output capability will be supplied by an on-line computer system and a conversation program called SPRINTER: Mod III. The model based system is designed to serve as a means of (1) gaining meaningful behavioral interpretations from test market data, (2) forecasting national sales levels before national introduction, (3) recommending improved product strategies, (4) recommending a GO, ON or NO

decision, and (5) identifying national introduction problems, recommending solutions to them, and generating revised sales forecasts.

THE MACRO BEHAVIORAL PROCESS MODEL

Model Development Criteria

In developing an information system model, explicit design criterion should be set. The introductory section of this paper has already specified the criterion of high behavioral content, but there are a number of ways of satisfying this goal. One method is to build a micro-analytic simulation.[17] The model form may contain 1000 market subunits and could specify in minute detail   the purchase decision in each unit. Another model form might be an aggregate set of multivariate equations, but   these more aggregate models are limited in their ability to consider behavioral phenomena.[18] In deciding upon a level of detail for a new product model the ease of estimation, testing, and solution must also be considered. In general, the ease of testing, estimation and solution decreases as the level of detail increases and drops sharply at the micro simulation level. However, as the level of detail increases, the behavioral content increases with a rapid increase at the micro level. To determine the best level of modeling detail, the decision problem and the constrain on the modeling must be considered. If the firm has few resources and little time, the model would be constrained to the macro level of detail. If the firm had a large budget and no time or personnel constraints, the model could assume any level. In this case, the desired level of problem solving detail would dictate the best modeling level. In the new product analysis and decision problem posed in this paper, this would argue for a more micro model since it is desirable to include the behavioral content of the adoption process and the

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[17]See [1]; [18]See [38],[19].

problem would require detailed output. In most new product cases, the budget and time constraints will preclude a micro-simulation, but would justify a model with a reasonably high level of detail if it could generate solutions to the marketing mix problem and lend itself to testing and estimation. Such a model would fall between the simulation and aggregate equation alternatives. This type of model might be called a "macro behavioral process" model. This model could have a high level of behavioral content, but it would be feasible to develop and operate on a limited budget.

With the goal of achieving efficiency and behavioral content in mind, a macro behavioral process new product model will be described. This model description begins by verbally defining the steps in the consumption process, then describing these steps for several depth of class groups, and finally mathematically specifying the model phenomena and the effects of controllable variables on the process.

Behavioral Processes

The basic process elements of the model are: (1) awareness, (2) intent, (3) search, (4) choice, and (5) post purchase behavior. In the awareness model, consumers are classified on the basis of their awareness to the brand, advertisements, specific product appeals, and word of mouth communication. These classifications represent exclusive hierarchal divisions. That is, people who are classed as brand aware are only brand aware. People who are ad aware are brand and ad aware, but not aware of any appeals. People classed as aware of a specific appeal of the product are aware of the brand, ad, and that specific appeal, but no other appeals. The assignment of people to these classes is based on a recall to the brand, ad, appeal, or a word of mouth recommendation. This scheme allows

selective perception and selective forgetting to operate since it classifies people by recall and different people are observed to recall different appeals after seeing the same ad. The distribution of people in the awareness classes reflects the effects of advertising expenditures in a given period, past advertising, product experience, and past receipt of word of mouth communication.

The intent model takes each awareness class and processes it to determine how many people from each class will display preference for the brand and intent to purchase it. The percent of people in a given awareness class who display intent to buy the product will depend upon the perceived compatibility and relative advantage of the product to the people who have the specific recall of that class. Although the model does not possess a specific learning mechanism it does monitor the overall behavioral response to advertising through the awareness to intent response.[19] It would be expected that the percent with intent would be higher in appeal recall classes than in the brand awareness class since specific appeal recall represents more perception of the product's relative advantage. The highest buying rates might be expected in the awareness class representing receipt of word of mouth recommendations since this group would be one in which the perceived risk is low. After the number of people intending to buy has been determined for each awareness class, they are added to get the total number of people with intent. These people now undergo a search effort in an attempt to find the product.

The search model determines if the product is available at the consumer's favored retail store. This availability is based on the percent of distribution obtained by direct company and wholesaler sales effort when given a particular middleman margin or "deal." If the brand is not available the consumer may delay choice and search at a different store.

If the product is available, the consumer with intent will choose the brand unless he is switched to another brand in the store. This switching is

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[19] See [27], [17], [18].

dependent upon the relative price and point of sales activity of the brand.
Those consumers with no intent before entering the store could purchase
the brand on the basis of the in store price, promotion, and communication.
If they purchase, they are added to the buyers who exercised their intent.

If a consumer buys a product, he may generate word of mouth recommenda-
tions or can respond to word of mouth inquiries by non-buyers. These exchanges
are particular in content and receivers are moved to new awareness and appeal
classes on the basis of receipt of new information and its internalization.
After each period, consumers experience forgetting. They forget selectively
from one appeal awareness class to another so cognitive dissonance can be
considered. After the completion of these post purchase phenomena of word
of mouth and forgetting, the consumers in each awareness class are returned
to the awareness model for the receipt of new communication and a repeat of
the consumption cycle. As the cycle is repeated, the model's parameters
such as trial rate are allowed to change so that the non-stationarity of
buyer response can be encompassed.

Depth of Class Effects

The five step behavioral process outlined in the previous paragraphs
takes place in each of five "depth of class" submodels of the total macro
behavioral process model. The submodels represent heterogeneous purchase
histories of the consumers based on the number of times they have used the
product. See Figure 1. The first is the trial model. All potential consumers
of the basic type of product who have not tried our brand of the product are in
this model. The total number of potential buyers of the product class is
influenced by the combined communication and promotion effort of the firms
in the industry. Consumers exit the trial model by a purchase of our brand

of the product and move to the preference model. In the preference model,
the consumer develops and displays his preference by additional purchases
of the brand. If the new product is purchased again, the consumer moves
to the loyalty I model where he either displays loyalty by a purchase and
moves to the loyalty II model, or makes no purchase and moves to the non-
loyal model. Return to the loyalty I model from the non-loyal model can be
made by another purchase of our brand. To enter loyalty II, a consumer must
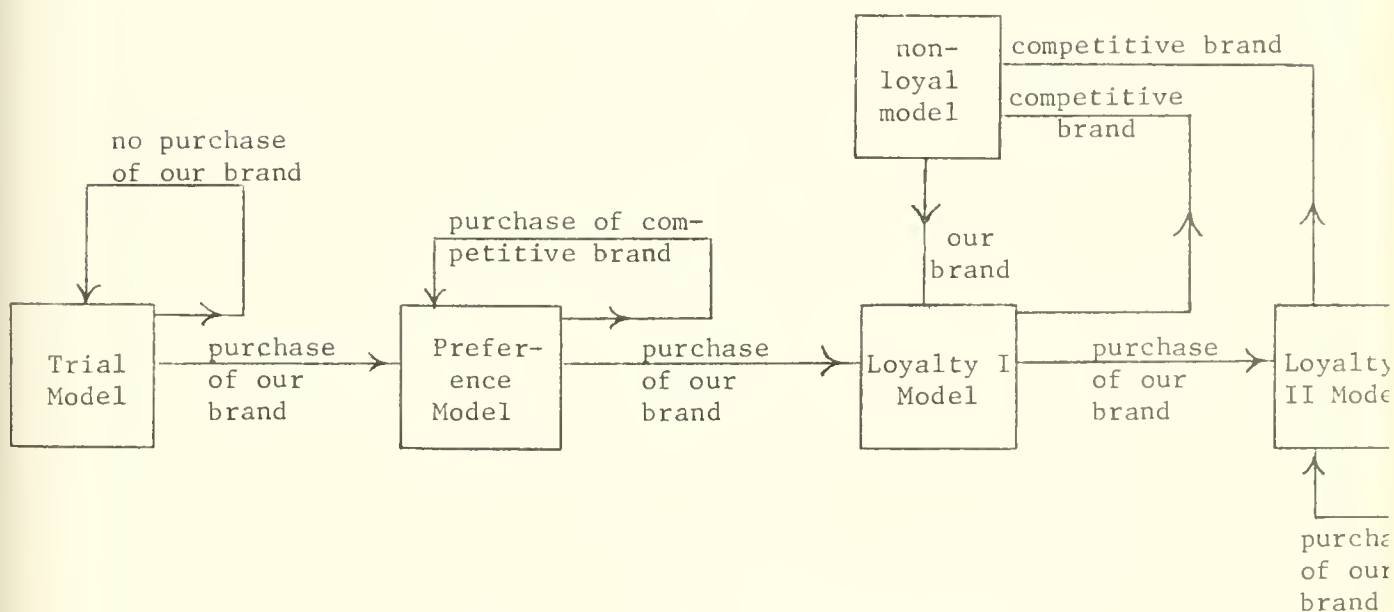have purchased at least three times.

FIGURE ONE

DEPTH OF CLASS MODELS

As the diffusion process proceeds more people will leave the trial model and move on to the preference and loyalty models. The rate of diffusion will depend upon the trial rate of the innovators and their post purchase behavior. As other adopter classes approach first purchase, the trial rate may fall. The degree of acceptance will ultimately depend upon the repeat purchase behavior in the preference and loyalty models assuming the trial rate is greater than zero. A successful product is characterized by a fast diffusion rate and a high degree of acceptance.

Mathematical Model

With this basic verbal description of the model, the mathematical detail of the trial, preference, and loyalty models can be more readily understood. Overall flow diagrams are included as a pedagogic aid.

Trial Model (See figure two): First, the number of people in the trial model must be specified. Since the depth of class models form a mutually exclusive and collectively exhaustive set, the number of people in the trial model is the current number in the total market for the product (i.e. industry) less the number remaining in the preference and loyalty models.

$$(1) \quad TRIAL_t = TNIND_t - NPREF_{t-1} - NLOYL1_{t-1} - NLOYL2_{t-1} - NNLOYL_{t-1}$$

$TNIND_t$ = number of people in industry of the product in period t

$NPREF_{t-1}$ = number of people in preference model in period t-1

$NLOYL1_{t-1}$ = number of people in the loyalty I model in period t-1

$NLOYL2_{t-1}$ = number of people in the loyalty II model in period t-1

$NNLOYL_{t-1}$ = number of people in the non-loyalty model in period t-1

The number of people in the industry for the product is forecasted to be some reference level, but it can be influenced by industry advertising expenditures or by the total number of samples of the new product sent by the firms in the industry.

(2) $TNIND_t = FNIND_t \cdot \overline{RADIND} \, (ADIND_t/FADIND_t) + (SMIND_t - FSMIND_t)$

$\cdot \, (1 - TNIND_t/PWORLD_t) \cdot ASMPUS$

$FNIND_t$ = forecasted reference number of people in the industry in period t

$\overline{RADIND}$ = advertising response function

$ADIND_t$ = actual industry advertising expenditure in period t

$FADIND_t$ = forecasted industry advertising expenditure in period t

$SMIND_t$ = total number of samples sent out by firms in industry in period t

$FSMIND_t$ = forecasted reference number of samples to be sent out by firms in industry in period t

$PWORLD_t$ = potential number of people who could possibly be a user of this product

$ASMPUS$ = percent of people who receive samples who use them and are pleased with product

This equation says the number in the industry is the forecasted number times a response function   which represents the effects of advertising levels different than forecasted plus the effects of samples when they are given in quantities other than expected. The advertising response function represents the proportionate change in the number of people in the industry as the ratio of actual to expected industry advertising expenditure departs from one. This allows a completely free format for defining the form of advertising response. The function would be defined by a large number of discrete entries. If a ratio did not fall on a discrete point, linearly interpolation would be used. The sampling effect in Equation 2 represents the fact that when someone not now

using our type of product receives a sample, uses it, and is pleased, he can be considered a prospective buyer. This part of the equation therefore states that the number of samples sent by all firms times the percent of people not now in industry times the sample usages rate represents a best estimate of the number of new people added to the industry through sampling at other than the expected level.

This sampling effect is important in many truely new products since it enables a person to experience trial without overcoming the perceived risk implied in undergoing the trial process of awareness, intent, search, and choice. The industry effects of such sampling may increase the total market as indicated in Equation 2, but it also has the effects of giving some customers of our brand a pseudo trial, so the number of people in the trial model for our brand should be modified for this effect. The number in the trial model after our firm's sampling is:

$$(3) \quad NTRIAL_t = TRIAL_t - SMFIRM_t \cdot (TRIAL_t / PWORLD_t) \cdot SAMPUS$$

$SMFIRM_t$ = number of samples sent by our firm in period t

$SAMPUS$ = percent of people who use sample and experience a pseudo trial

The people who experience trial due to sampling are moved on to the preference model.

The awareness section of the trial model describes the effects of advertising in creating awareness. The number of newly aware people whose awareness was created by advertising is the number of people unaware in the trial model times the percent of people becoming aware at various advertising levels.

Figure Two - Overall Trial Model Flow Diagram

those people remaining in trial model last period

number of people in industry with no use experience with our brand in period t ($TRIAL_t$, Eq. 1*)

number of people not receiving sample

number of people receiving sample

do not use sample

use sample

number in trial model after sampling ($NTRIAL_t$ Equation 3)

to preference model in period t

number of people in each specific awareness class in period t ($NAWT_{t,J}$, Equation 5)

do not receive coupon

receive coupon

number of people in each awareness class with intent to try brand ($NTRY_t$, Eq. 6)

number of people with no intent to try brand

number of people with no intent to redeem coupon

number of people with intent to redeem coupon

do not find our brand

find our brand when shopping ($TFIND_t$, Eq. 8)

shop in store not carrying our brand

shop in store carrying our brand

do not find brand

do find brand

number who do not buy in store

number who buy in store ($NTBUY_{t,S}$, Eq. 9)

number who do not buy in store

number who buy in store

number who do not buy in store

number who buy in store

word of mouth generation

to preference model in t + 1

number in each specific awareness class after forgetting ($NAWTF_{t,J}$, Eq. 10)

remain in trial model in t+1

number in each specific awareness class after word-of-mouth exchange (NAWTFW, Eq. 11)

Awareness

Intent

Search

Choice

Post Purchase

* equation numbers are given where mathematical equations are defined in text, others are verbally described in text

(4) $DADAWT_t = (NTRIAL_t - TADAWT_{t-1}) \cdot \overline{RADAWT} (ADFIRM_t/FADFRM_t)$

$DADAWT_t$ = number of people newly aware resulting from our advertising level ($ADFIRM_t$) in period t

$TADAWT_{t-1}$ = number of people remaining aware at the end of the last period

$\overline{RADAWT}$ = response function representing the percent of people aware of our brand, ads, or appeals at our advertising expenditure level ($ADFIRM_t$) compared to the reference level ($FADFRM_t$)

All the people will not gain the same awareness on seeing an ad. Some will be aware of specific appeals while others will be aware of only seeing the ad and have no specific recall. For example, specific awareness class designations for a new soap may be 1 for unaware, 2 for ad aware only, 3 for aware of cleaning power, 4 for aware of gentleness appeal, 5 for aware of gentleness and cleaning power. The number of people in each awareness class is the number remaining after last period plus the new people made aware of some appeal times the percent of these who are made aware of a specific appeal.

(5) $NAWT_{t,J} = \overline{NAWTFW}_{t-1,J} + DADAWT_t \cdot \overline{RADAPT} (ADFIRM_t/FADFRM_t) \cdot \overline{RAPSPT} (ADFIRM_t/FADFRM_t, J)$

$NAWT_{t,J}$ = number of people in appeal awareness class J

$NAWTFW_{t-1,J}$ = number of people in appeal awareness class J at the end of the last period after forgetting and word of mouth transfer

$\overline{RADAPT}$ = response function representing percent of people newly aware who become aware of some appeal at our advertising level ($ADFIRM_t$) relative to our reference level ($FADFRM_t$)

$\overline{\text{RAPSPT}}$ = response function representing percent of people who are aware of _some_ appeal who become aware of _specific_ appeal J

The response function $\overline{\text{RADAPT}}$ and $\overline{\text{RAPSPT}}$ are functions of advertising because as advertising expenditures are increased, the relative awareness class compositions may change. The awareness classes defined in the trial model include all people in the trial model, so the people aware of ads only (no specific content recall) is the difference between the total ad awareness and the sum of the specific appeal awareness classes. The population of brand aware only is the difference between total awareness and ad awareness. The remainder of the people in the model are in the unaware class.

Awareness must now be translated into intent. The number with intent to try is the sum of the number with intent to try in each awareness class, where each class has its own intent rate, modified by the effects of competitive advertising.

(6) $NTRY_t = \sum_J NAWT_{t,J} \cdot TRATE_{t,J} \cdot \overline{RACOMT} \left((TCPTA_t / ADIND_t) / (FTCPTA_t / FADIND_t) \right)$

$NTRY_t$ = number of people with intent to try in period t

$TRATE_{t,J}$ = percent of people in awareness class J who intend to try in month t

$\overline{\text{RACOMT}}$ = response function describing the effects of total competitive advertising ($TCPTA_t$) as a percent of total industry advertising ($ADIND_t$) relative to the expected proportion of competitive advertising ($FTCPTA_t / FADIND_t$)

A common new product marketing tool is the use of coupons offering a price reduction. To encompass this marketing mix element, the model segments those who receive a coupon and have intent to redeem it (see figure two). $NTRY_t$ therefore does not include those who received a coupon and intent to take it to the store.

The people with intent now search for the product by shopping at
their favored type of retail store (e.g. drug, food, variety.) Their
ability to find it will depend upon the number of stores carrying the product
which in turn depends upon our sales effort on stores not now stocking the
product and the middleman margin or "deal" offered the retailer relative to
competitive "deals."

(7) $AVAIL_{t,S} = AVAIL_{t-1,S} + SLCAL_{t,S} \cdot (1 - AVAIL_{t-1,S}/NSTOR_S) \cdot$

$\overline{RDEAL}$ $(DEAL/ADEAL) - DROP_{t,S}$

$AVAIL_{t,S}$ = number of stores of type S that stock our product in period t

$SLCAL_{t,S}$ = number of sales calls on store type S in period t

$NSTOR_S$ = total number of stores of type S in period t

$\overline{RDEAL}$ = response function representing the percent of stores who

stock our product at a specific middleman deal (DEAL)

relative to the average competitive deal (ADEAL)

$DROP_{t,S}$ = number of stores who drop our product when its sales are

below their expectations

= $AVAIL_{t-1,S} \cdot \overline{RDROP}$ $(RTHRU_S/FTHRU_S)$ where $\overline{RDROP}$ is a response

function representing the percent of stores who will drop

our product when the average of the last two months sales

$(RTHRU_S)$ is below expectation $(FTHRU_S)$. When $RTHRU_S >$

$FTHRU$, $\overline{RDROP}$ reflects out of stock situations.

The drop term is added to reflect the shrinkage in distribution that occurs
if the product sales growth is not satisfactory. When the percent of stores
carrying the product is calculated, the number of people who have intent to
try and find the product is the number who find the product at their favorite

retailer plus the number who will look in another store for the product if it is not available in their favorite store.

$$(8) \quad TFIND_t = \sum_S PSHOP_S \cdot NTRY_t \cdot AVLPCT_{t,S} + \sum_S \sum_{SS} PSHOP_S \cdot (1 - AVLPCT_{t,S})$$
$$\cdot NTRY_t \cdot PSWST_{S,SS} \cdot AVLPCT_{t,SS}$$

$TFIND_t$ = number of people who have intent to try and find the product

$PSHOP_S$ = proportion of people who deem store S as their favored retailer for this type of product

$AVLPCT_{t,S}$ = percent of stores of type S carrying the product

$\quad\quad\quad$ = $AVAIL_{t,S}/NSTOR_S$

$PSWST_{S,SS}$ = proportion of people who do not find the brand at their first choice store who will switch to store SS

The people who find the product and have intent now must make an in store decision to either buy the product or not. At this point the consumer perceives the self price and must determine if the price relative to existing products is acceptable. This may be viewed as a weighing of the relative advantage of the new product versus the relative price and risks of trial. The risks of trial may be buying a product that does not work or may be more widely based social risks. These phenomena can be structured by stating that the percent of people who exercise their intent will depend upon the new product price relative to the price standard for similar old products or the expected price of a completely new product. The number actually purchasing is:

$$(9) \quad NTBUY_{t,S} = TFIND_{t,S} \cdot \overline{RPDIFT} \, ((PR_{t,1} - SPR_t)/SPR_t) \cdot \overline{RPOP} \, (SD_t/FSD_t)$$

where $\overline{RPDIFT}$ is a response function representing the percent of people who will exercise their intent when presented with our specific price $(PR_{t,1})$ relative

to the price standard (SPR_t). $\overline{RPOP}$ is a response function representing the point of purchase effects of our special displays (SD_t) relative to the expected level of our display activity (FSD_t). Those people with a coupon would perceive a lower shelf price and are described by an equation similar to Equation 9 with the price equal to the shelf price less the coupon "price off" amount.

In some cases the price response expression may not be needed because of the particular nature of a product. In such a case it could be removed by setting its value to one for all prices. It is the judicious choice of functions and phenomena to be included or excluded that makes the behavioral process model effective. As a further example, Equation 9 implies people with no intent to try will not purchase. In some products the instore environment may actually create awareness and intent. In such a case the number who try should be increased by the percent of people with no intent when intering the store   are made aware, develop intent, and purchase the product because of the point of purchase display. Usually this will be a small effect but in some product classes it may be justifiable to add more detail because of the behavioral process characterizing the product and therefore this option is in the model.

The total number of triers is the sum of the triers in each store type. After trial, the two post purchase phenomena of forgetting and word of mouth generation may take place. Those people who purchase are moved on to the preference model and those who remain experience forgetting. The number of people in a specific awareness class is the number remaining after purchase less those who forget to lower awareness classes plus those who forget to the class from higher awareness classes.

(10) $\quad NAWTF_{t,J} \; = \; NAWTA_{t,J} + \sum_{\substack{K \\ K>J}} NAWTA_{t,K} \cdot RFRGT_{K,J} - \sum_{\substack{K \\ K<J}} NAWTA_{t,J} \cdot RFRGT_{J,K}$

$\text{NAWTF}_{t,J}$ = number of people in awareness class J after forgetting in the trial model

$\text{NAWTA}_{t,J}$ = number of people in awareness class J after trial purchasers have been moved to the preference model

$\text{RFRGT}_{J,K}$ = percent of people who forget from awareness class J to awareness class K in trial model

$\text{RFRGT}_{K,J}$ = percent of people who forget from class K to awareness class J in trial model

The trial model section of the word of mouth process is conceptualized by two mechanisms: (1) buyers initiate word of mouth about appeal J, or (2) non-buyers request information about appeal J. The total amount of word of mouth for all models is the sum of the buyer initiated word of mouth and the non-buyer requests for word of mouth communication which reach someone with some awareness about the appeal. This pool of word of mouth information is assumed to fall randomly upon the awareness classes. The amount received by a class is proportional to its size compared to the total industry. If they receive information about a higher awareness class, they move to that class. If they receive information they already possess, they remain in the same class. An awareness class population after word of mouth is then the original value plus those who have moved to the class from lower awareness classes less those who have moved to higher classes. The number of people is:

$$(11) \quad \text{NAWTFW}_{t,J} = \text{NAWTF}_{t,J} - \sum_{\substack{K \\ K>J}} \text{WOM}_{t,K} \cdot (\text{NAWTF}_{t,J}/\text{TNIND}_t) + \sum_{\substack{K \\ K<J}} \text{WOM}_{t,J}$$

$$\cdot (\text{NAWTF}_{t,K}/\text{TNIND}_t)$$

$\text{WOM}_{t,K}$ = total number of word of mouth exchanges about appeal K in pool
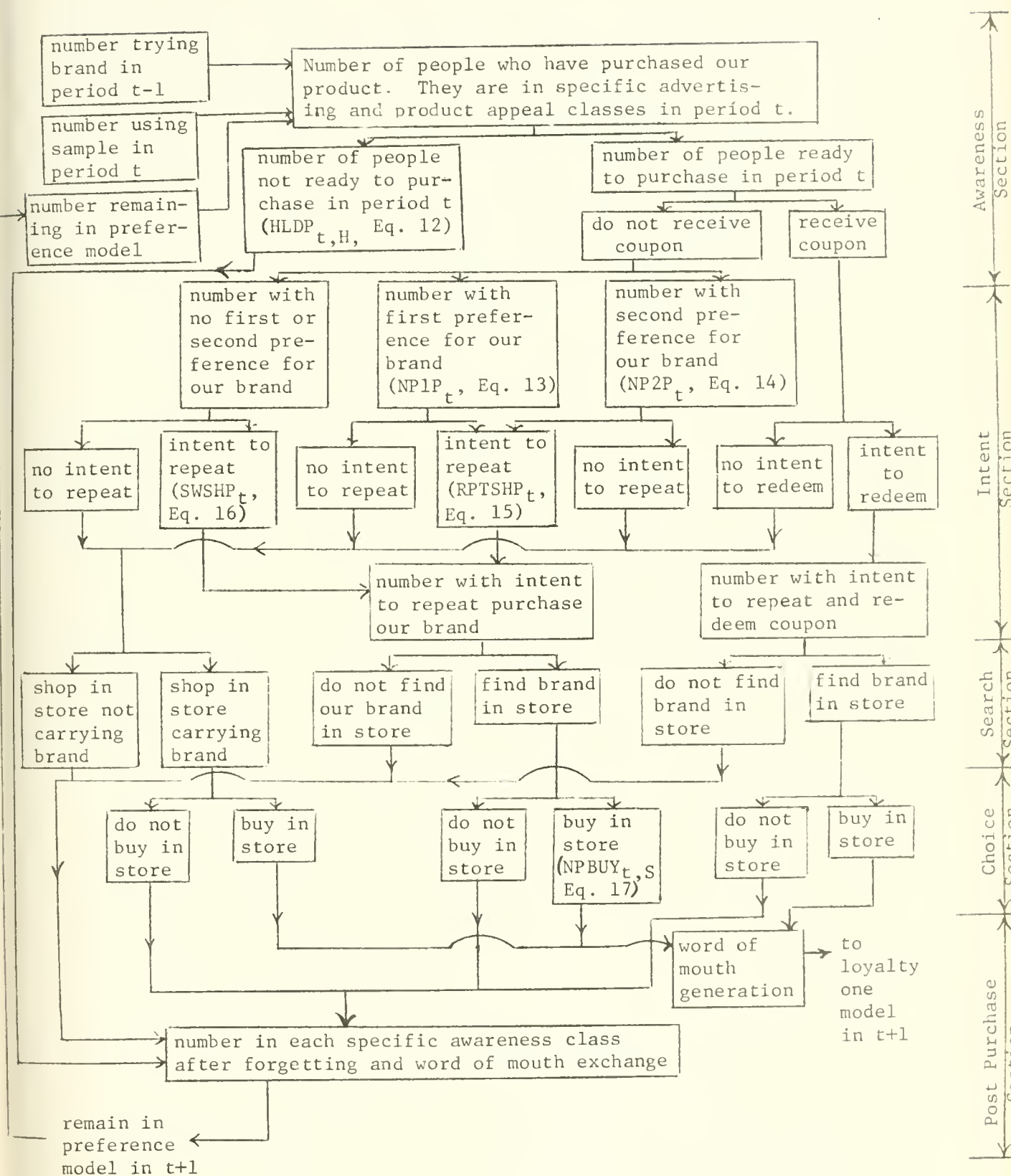
TNIND_t = total number of people in industry in period t

This number of people in each awareness class is input to the next period (see Equation 5).

Preference Model (See Figure Three): In order to reach the preference model the consumer must have tried the product. He can leave the model by repurchasing and can remain in it only by not repurchasing our brand. The number in the preference model is the number in the model last period less those who purchased in the preference model last period plus those who tried last period plus those who used a sample this period. (see Figure One). Since all the people in the preference model have used the product, they will not be completely unaware of the product and most will be aware of some specific characteristic as a result of using the product. Some will not like the brand while others will have a very positive experience and still others may be aware of some characteristics of the brand but have not formed a definite opinion. Therefore it is meaningful to again classify people by their awareness to specific product and advertising appeals with the understanding that one appeal class will represent negative and one positive use experience. Although the trial product use is the prime determinant of a person's awareness, advertising can still play an important role in products where the appeals are sociological or psychologically based. Here advertising is needed to reinforce awareness to these utilities. Even positive use may be reinforced since advertising plays a role in reducing cognitive dissonance. Therefore, the new awareness of the product and numbers in each awareness class are functional on advertising although this function should be less responsive than the corresponding functions in the trial model. Equations similar to (4) and (5) parameterized for the preference model are used to define the awareness classes.

All people in the preference model may not have the need to re-purchase in the next period since consumers use the product at varying

Figure Three - Overall Preference Model Flow Diagram

number trying brand in period t-1

Number of people who have purchased our product. They are in specific advertising and product appeal classes in period t.

number using sample in period t

number of people not ready to purchase in period t ($HLDP_{t,H}$, Eq. 12)

number of people ready to purchase in period t

number remaining in preference model

do not receive coupon

receive coupon

number with no first or second preference for our brand

number with first preference for our brand ($NP1P_t$, Eq. 13)

number with second preference for our brand ($NP2P_t$, Eq. 14)

no intent to repeat

intent to repeat ($SWSHP_t$, Eq. 16)

no intent to repeat

intent to repeat ($RPTSHP_t$, Eq. 15)

no intent to repeat

no intent to redeem

intent to redeem

number with intent to repeat purchase our brand

number with intent to repeat and redeem coupon

shop in store not carrying brand

shop in store carrying brand

do not find our brand in store

find brand in store

do not find brand in store

find brand in store

do not buy in store

buy in store

do not buy in store

buy in store ($NPBUY_{t,S}$ Eq. 17)

do not buy in store

buy in store

word of mouth generation

to loyalty one model in t+1

number in each specific awareness class after forgetting and word of mouth exchange

remain in preference model in t+1

Awareness Section

Intent Section

Search Section

Choice Section

Post Purchase Section

rates. These different purchase frequencies are included in the model by defining holding class that contain the number of people who have will be ready to purchase in H periods.

(12) $HLDP_{t,H} = HLDP_{t-1,H+1} + (TBUY_{t-1} + SMFIRM_t \cdot SAMPUS$

$(NTRIAL_t / PWORLD_t)) \cdot FREPR_H$

$HLDP_{t,H}$ = number of people who will be ready to purchase in H periods, H = 1, ..., h

$FREPR_H$ = frequency of purchase defined by the percent of consumers purchasing every H+1 months

This equation reflects the fact that all consumers do not buy each period. The distribution of purchase rates is used to place people in holding classes as they enter the preference model by a trial ($TBUY_{t-1}$), by sampling. The number in the preference model less the number of people in some holding class is the number of people who are ready to purchase in period t.

For those ready to purchase, awareness must now be translated into intent to repurchase. Those who receive a coupon are separated (see Figure Three) and the others are processed by an awareness to preference and preference to intent process. The percent of people in each awareness class with first preference will vary between classes and the total number with first preference is the sum of the number with first preference in each awareness class.

(13) $NP1P_t = \sum_J NAWP_{t,J} \cdot P1RATE_{t,J}$

$NP1P_t$ = number with first preference for brand

$P1RATE_{t,J}$ = percent of people in awareness class J who have a first preference for the product

$NAWP_{t,J}$ = number aware of appeal J in period t in preference model and ready to buy

Similarly the number with a second preference for the brand is

$$(14) \quad NP2P_t = \sum_J NAWP_{t,J} \cdot P2RATE_{t,J} \quad \text{where}$$

$P2RATE_{t,j}$ = percent of people in awareness class J who have a second preference for the product

The number of these people who convert their preference into intent will probably be less than 100 percent and will be influenced by competitive advertising efforts. Although the product use experience was successful and adequately reinforced by our advertising, competitors may cause consumers to buy their product rather than ours through their relative advertising pressure. The number of people in the preference model who intend to repeat purchase and who would purchase some product in period t is:

$$(15) \quad RPTSHP_t = (NP1P_t \cdot BRP1P + NP2P_t \cdot BRP2P) \cdot \overline{AREL} ((ADFIRM_t /$$
$$TCPTA_t) / (FADFRM_t / FTCPTA_t))$$

$BRP1P$ = percent of people with first preference who are expected to convert that preference into intent to repurchase.

$BRP2P$ = percent of people with second preference who are expected to convert that preference into intent to repurchase

$\overline{AREL}$ = response function representing the effects of competitive advertising by the proportionate reduction in the number intending to repurchase at our level of advertising ($ADFIRM_t$ relative to total competitive advertising ($TCPTA_t$) compared to the forecasted ratio ($FADFRM_t / FTCPTA_t$)

The development of intent to buy our brand in the preference model may come about not only from a preference for our brand. Some people may intend to buy our brand by switching from their preferred brand. Although this may not be a large number of people, it is significant in understanding the brand switching that takes place after trial especially since competitive advertising affects the rate of switching. The number of switchers with intent to buy our brand is:

$$(16) \quad \text{SWSHP}_t = (\text{NPREF}_t - \text{NP1P}_t - \text{NP2P}_t) \cdot \text{SWRFK} \cdot \overline{\text{ARELK}} \,((\text{TCPTA}_t \,/\, \text{ADIND}_t) \,/\, (\text{FTCPTA}_t \,/\, \text{FADIND}_t))$$

NPREF_t = number of people in preference model ready to buy in period t, but with no intent to redeem a coupon

SWRFK = percent of people with no preference for our brand who develop an intent to buy our brand at reference competitive advertising

$\overline{\text{ARELK}}$ = response function reflecting proportionate change in switching rate as total competitive advertising (TCPTA) as a percent of industry (ADIND_t) varies from the predicted reference ratio ($\text{FTCPTA}_t \,/\, \text{FADIND}_t$)

The total number of people intending to repurchase our brand is the sum of the repeaters and switchers (NPSHP_t) plus those with a coupon and an intent to redeem it

The preference model consumers who have intent now search for the brand. Since they tried the product before entering this model, if they return to the same store they will find the product, unless the retailer has dropped it. The expression for the number who find the product is similar to Equation (8) except that it applies only to those who do not return to the same store or whose regular store has dropped the product. The result is the number of people with intent who find the product at a particular store.

Once in the store the preference model buyer is influenced by the instore price and display. The proportion who carry out their intent and purchase is presumed to depend upon the relative perceived instore effectiveness of each brand. Instore displays, facings, and price may also induce people with no intent for repurchase to buy our brand. The number of actual purchases in the preference model by those with intent and no coupon is:

$$(17) \quad NPBUY_{t,S} = TSHOP_{t,S} \cdot K \cdot [(PR_{t,1,S}^{SPR1S} \; FA_{t,1,S}^{SFA1S} \; SD_{t,1,S}^{SSD1S} \; / \; \sum_i PR_{t,i,S}^{SPRiS} \; FA_{t,i,S}^{SFAiS} \; SD_{t,i,S}^{SSDiS})^{EI}]$$

$TSHOP_{t,S}$ = number of people entering store of type S carrying our brand with intent to purchase our brand (but with no coupon)

$PR_{t,i,S}$ = price of brand of firm i in store S in period t

$FA_{t,i,S}$ = number of package facings exposed on the shelf of brand of firm i in store S in period t

$SD_{t,i,S}$ = percent of stores of type S that have special displays for firm i's brand in period t

K = scale constant

$SPRiS$ = sensitivity of price for firm i's brand in store S

$SFAiS$ = sensitivity of facings for firm i's brand in store S

$SSDiS$ = sensitivity of special displays for firm i's brand in store S

EI = elasticity of in store environment for consumers with intent to buy our brand

An equation similar to Equation 17 with a different elasticity defines the number of preference model consumers with no intent in a store carrying our product, but who buy our brand. This form is also used to describe the behavior of people with a coupon (and therefore a lower price) in the store (see Figure Three).

The number of facings is determined by the effectiveness of our brand relative to the middleman's expectations. If the retailer finds sales much

higher than expected he will allocate additional shelf facings to our brand. In this way the instore environment is affected by a combination of our controllable variables and the retailer's decision rules.

The total number of people who buy our brand is the sum of the buyers in each store. These buyers undergo forgetting and word of mouth by the same process as trial buyers. The process is described by Equations (10) and (11) when these equations are parameterized for preference rather than trial buyers.

The preference buyers who buy our brand in period t are moved to the loyalty one model. Those who do not buy our brand are returned to the beginning of the preference model after forgetting and word of mouth exchange.

Loyalty Model: In the loyalty model the level of detail in considering the behavioral process is lower than in the preference or trial model, because in this model it can be assumed that consumers have a positive attitude towards the brand and have established a source of supply. The number in the loyalty one model are those who were in the model last period plus those who repurchased in the preference model less those who purchased competitive brands or our brand in the loyalty one model plus those who repeat purchased our brand in the non-loyal model. (See Figure One.)

The number of people intending to buy our brand this period is the number who have a purchase opportunity this period times the repeat rate for loyal buyers less the effects of competitive advertising in winning over part of our loyal buyers. Assuming the loyal buyer has a source of supply for our brand, the number who actually purchase is the number with intent decreased by instore effects. In this model it is presumed that facings and displays are not important, but that relative price changes could cause our loyal buyers to switch to other brands. For example, a large price off deal by a

competitor could decrease our rate of repurchase. The number of loyalty one buyers is:

$$(18) \quad BUYL1_t = (NLOYL1_t - \sum_H HLDL1_H) \cdot REPT1 \cdot \overline{AREL1} \, (ADFIRM_t / (ADIND_t / QFIRM_t)) \cdot \overline{PREL1} \, (PR_{t,1} / (\sum_i PR_{t,i} / QFIRM))$$

REPT1 = percent of loyalty one consumers who intend to repeat purchase our brand at reference price and advertising levels

$NLOYL1_t$ = number of people in loyalty one model in period t

$HLDL1_H$ = number of people who will be ready to purchase in H periods (See Equation 12 for analogous calculation)

$\overline{AREL1}$ = response function representing the effects of our advertising ($ADFIRM_t$) relative to the average level of advertising per firm ($ADIND_t / QFIRM_t$, where QFIRM = number of firms in industry in period t) by the proportionate reduction in the intent rate in the loyalty 1 model

$\overline{PREL1}$ = response function representing the effects of our price ($PR_{t,1}$) relative to the average price by the proportionate reduction in our repeated loyalty 1 model buyers in the store

The buyers of our brand in this model proceed on to the loyalty two model while buyers of competitive brands go to the non-loyal model. The loyalty buyers of our brand can generate word of mouth which is added to the total pool of word of mouth. Loyalty one buyers are all assumed to be aware of some positive product features because of two purchases of the brand, so those remaining in the model are not subject to forgetting; rather they are considered to retain awareness to at least one positive appeal.

The loyalty two model is structured in the same way as loyalty one. The number of people in the model is the number who were in the model last

period plus those who purchased in loyalty one last period less those who pur-
chased a competitive brand last period in the loyalty two model. In the loyalty
two model it can be expected that the repeat rate will be higher and the response
functions will be less sensitive then in the loyalty one model. The non-loyal
model contains those people who did not repeat in loyalty one or two. It is
similar to Equation 18 with different response functions and lower repeat rates.

Cost, Profit and Risk Models: After the total number of buyers has
been determined, the total revenue and total cost can be determined by usual
accounting methods and by the application of an appropriate cost function.
The profit attributable to the brand, however, may not be the difference
between these revenues and cost. If the new product is interdependent with
other brands offered by the firm the loss or gain in profits of the other
brands should be considered to calculate differential profits.[20] The differential
profit can be obtained by subtracting the profit that would have been earned
by the existing product if consumers had not tried or repeat purchased the
new product instead of the old product. Conversely, if the new product is
complementary to existing products, the additional profit earned by old products
because of consumers buying the new product should be added to the new product's
accounting profit to determine differential profits. The differential profits
reflect the improvement in the company's position due to introducing the product.

The risk associated with the brand can be determined by describing
distributions about the input parameters and running a large Monte Carlo
analysis to determine the distribution about total differential profits or
by describing a distribution about expected sales and translating it into a
differential profit distribution. The risk-return-investment balancing could
be made by examining the probability of achieving a target rate of return or
target payback.[21] If an appropriate criterion is set the model will recommend
a GO, ON, or NO decision for the brand, given a particular introduction strategy.

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[20] See [38]; [21] See [38], [9].

That is, if the probability of achieving the target rate of return is greater than the GO level, a GO decision is made. If the probability is less than the GO level, but above the NO level, an ON decision is made and more information is collected or efforts are directed at improving the product. If the probability of achieving the target rate of return is less than the NO level, the product is rejected.

Finding the "Best" Strategy

The model described in the previous sections is designed to yield normative recommendations about the introductory strategy for the product. That is, what values should be set for the controllable variables of price, advertising expenditures, middleman deal, number of sales calls, and number of samples? These variables have been directly linked to the behavioral diffusion process in the equations in the last sections so that alternatives can be evaluated. The design criteria were to build a model that could be efficiently searched for the best strategy alternative, but still retain the behavioral richness of the consumption process. In establishing the level of detail necessary to accomplish the first objective, compromises had to be made. In almost all sections of the model more detail could be justified by a more micro level consideration of the process. For example, a number of market subsegments that follow defferent decision processes could be specified. The number of segments would increase the computer run times for the model, so the additional detail would have to be traded off against more computer expense in evaluating alternatives. Similarly retailers could be divided into directly serviced and indirectly serviced retailers, if the particular product could justify such additional detail. The detail in each of the micro-models was judiciously chosen to ensure the ability to search for best solutions with a reasonable expenditure of funds. The model is felt to be at efficient and sufficient level of detail, but certain frequently

purchased consumer goods may require additional depth because of behavioral peculiarities associated with the product.

In order to find the best or a good strategy for this model, iterative techniques must be utilized since the more analytical and algorithmic techniques are not applicable to a non-linear, discontinuous, dynamic model such as this one. In reviewing iterative techniques, a number of mechanical heuristics are available.[22] In the introduction of a new product, however, there is a potential heuristic in the brand or new product manager. He has lived with the brand's development and the product market and is a valuable subjective source of good strategies. This man heuristic can be tapped through a simple on-line program which asks him to specify initial values, ranges, and increments within the range for each variable.[23] These values are run in all combinations and the best results are reported back to the manager. He then can specify new values, ranges, and increments for evaluation. In this way the man uses his "good business judgments" to guide the search to good and sometimes best solutions in a reasonable number of steps. Experience with this macro behavioral process model indicates that about ten alternatives could be evaluated in one minute on a IBM7094 computer so that with a reasonable expediture of funds (say less than $1000) a good or perhaps best strategy can be found.

It is also useful to generate profit payoffs for the product under alternative competitive environments. This payoff matrix could be analyzed by game theory or Bayesian means to find the best strategy given possible competitive strategies. The model has the capability to accept alternate adaptive rules for competitors (e.g. follow, independent).

It is at the best strategy that the product should be evaluated. Then it can be assured that a good product will not be rejected because of

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[22]See [41]; [23]See [39].

a poor strategy decision. At this point, the functions identified for the model are to predict sales and profits for the new product, identify the profit maximizing strategy for the product, and recommend a GO, ON, or NO decision for the brand.

The Model and Adaptive Control in National Introduction

If the product receives a GO decision, its national introduction is initiated. During national introduction the macro behavioral process model serves an important function in diagnosing problems in national introduction, generating updated sales forecasts, and recommending solutions to the problems. The national introduction can be plagued with problems from at least four sources. First, consumers are fickle and their behavioral responses (e.g. preferences, intents, or awareness rates) may change from the test levels by the time the product reaches the national market. Second, competitors may change their strategies upon national introduction. Third, the test market cities may not have accurately measured the market phenomena. Fourth, there may be a failure in the execution of the national plans by the firm (e.g. distribution goals not obtained by the sales force.) These sources of change could produce undesirable or desirable sales trends. For example, preference rates could shift away from the product or towards it. Since a number of errors could occur simultaneously, observing only sales or market shares could mask many problems. The behavioral process model enables decision makers to monitor micro level consumer process elements (e.g. recall, intent) and determine if these behavioral responses are different than those observed in test. Errors in execution of the firm's plans could be observed in the levels of the controllable variables and their results (e.g. availability and awareness levels.) Competitors' changes could be monitored in changes in the level

of their controllable variables. If any changes occur in the controllable variables or in the behavioral responses, the model should be run with the updated values to see if these values accurately predict the current sales level. If they do, one can be reasonably certain that the behavioral changes identify the problem. This micro level approach to problem finding is different than observing only the market share or sales level and assuming no problems exist if it is satisfactory. The superficial consideration of problem identification can lead to a failure to identify basic consumer response problems that may lead to substantially different results in the future.

The macro behavioral process model supported by an adequate data bank can diagnose problems in the national introduction based on early sales and behavioral data. After the changes in response or variation of the controllable va iables have been found, the model parameters and response functions should be updated and conditional forecasts generated. This is an adaptive use of the macro behavioral process model.[24] The updating could take a number of forms. First a parameter could be discretely changed to the observed value if the new value represents a discrete competitive change or if the firm realizes it had made a mistake in measuring or interpreting the test data. A more common type of updating will be the combining of the new data with prior data. This kind of updating is particularily convenient if a Beta distribution fits the prior distribution of the behavioral response rates.[25] A more simple approach is to smooth the new data with old data by an appropriate smoothing constant. If this constant is chosen correctly it can be used to carry out the Bayesian updating procedure.[26]

After the appropriate updating has been carried out, a revised forecast can be generated. But this is not the end of the model's usefulness. The

[24]See [20]; [25]See [24]; [26]See [20].

revised model parameters can be searched to find the best response to the

changes. For example, if trial rates are higher than expected, but repeat

rates are lower, what is the best level for advertising? This question

could be answered by searching the model on the basis of the revised parameters

to find the most profitable revised national strategy. Given the new definition

of a strategy, procedures to collect additional information by observation or

experimentation should be instituted so the firm can adapt to future changes

in the market environment. The use of the model as an adaptive mechanism

gives it a potential to not only improve the GO national decision process,

but also the national introduction itself.

THE DATA BANK

The behavioral process model outlined in the previous section requires

a large amount of input. This input is at the behavioral process level and

must be drawn from a substantial data base. This section will outline the

data base needed to support the frequently purchased new product analysis.

The data base available for the GO national decision of a new consumer

product is the information that can be collected during test marketing of

the product. Usually the brand is marketed in a number of cities and if

adequate information gathering procedures are instituted, the input demands of

the model can be satisfied. The following types of data collection instruments

are needed:

    (1) store audit data

    (2) special awareness surveys

    (3) consumer panel data

    (4) salesmen's call reports

    (5) audits of advertising media

    (6) the firm's internal records

See Table One for some of the input usage of this data.

The store audit data should be a representative sample of the stores in the test cities. This will allow retail sales levels and market shares (if competitive products exist) to be determined. The audits should monitor sales, inventory, price, shelf facings, special displays, and out of stock conditions for the brand and its competitors in all types of stores. By examining this data on a disaggregated basis, it will be found that similar types of stores present different instore environments (e.g. different prices, number of facings, special displays.) These historical differences may supply the basis of estimating the sensitivity of sales to different prices or special displays. The retail sales levels in the different cities are also useful in determining the effects of alternate advertising levels that may exist between cities and over time. It would be desirable to have the differences result from controlled experiments, and this should be done unless budget restrictions preclude such expenditures.[27] The value of experimental data over observational data can be accessed by examining the confidence distributions about the parameters as reflected in the risk of the product (i.e. standard deviations of the differential profit distribution) and the sensitivity of the expected profit to the parameter's value. If the profit is very sensitive to the parameter, resources should be devoted to setting up controlled experiments. If observational data is relied upon, the risk of the project will be higher and an ON decision (collect better information) will result if this risk level precludes a GO decision. Although it is tempting to specify an ideal data base and therefore reduce the risk to almost zero, a more mature managerial approach is to specify a sufficient data base and only carry out extensive experimental studies if an ON decision is reached and a sensitivity analysis indicates the information could be useful in reducing the risk.

[27] See [2].

TABLE ONE

DATA BANK AND STATISTICAL BANK INPUT REQUIREMENTS

MODEL INPUT[d]	DATA BANK REQUIREMENT	STATISTICAL BANK CAPABILITY REQUIREMENT
$\overline{\underline{RADIND}}$ (2)* $\underline{RPDIFT}$ (9) RPOP (9) SPRiS (17) SFAiS (17) SSDiS (17) EI (17) $\underline{FNIND}$ (2) $\overline{RDROP}$ (7)	Audit of Stores in Test Market Cities	Regression General Classification and Analysis Program Non-Linear Numeric Estimation
TRATE (6) FREQ (16) SWRFK (16) $\underline{REPT1}$ (18) AREL1 (18) PREL1 (18) FNIND (1) SAMPUS (1,3)	Consumer Purchase History Panel in the Test Cities	General Classification and Analysis Program
$\overline{\underline{RADAWT}}$ (4) $\underline{RADAPT}$, RAPSPT (5) RACOMT (6) RFRGT (10) P1RATE (13) $\underline{P2RATE}$ (14) $\underline{AREL}$ (15) ARELK (16) WOM (11) SAMPUS (2,3) PSHOP (8) PSWST (8) BRP1P, BRP2P (15)	Special Awareness, Preference, Intent, and Usage Questionnaires Call Back Questionnaires	Regression General Classification and Analysis Program
$\overline{\underline{RDEAL}}$ (7)	Salesmen's Call Reports	Classification Analysis
ADIND (2,6,18) TCPTA (6,15,16)	Audits of Test City Media	
Advertising and Production Costs	Accounting Data	Classification

*Equation numbers are in parentheses

[d]This list only includes parameters given in the text equations, but other parameter are dealt with in an analogous manner.

Special questionnaires are useful in obtaining awareness and attitudes of consumers in the test cities. These should be administered each period and record the specific recall people have to advertising appeals, the word of mouth they received and its content, their preferences for the brands in the product class, their usage experiences, their intent to repeat or try, and their shopping habits. These data can be the basis of estimating awareness levels and the composition of specific appeal classes. If advertising varied it can be used to estimate the awareness response to advertising expenditure. The longitudinal awareness levels obtained from such data can be useful in estimating forgetting rates. The preference and intent data will be basic to estimating preference rates and the transformations to intents. If competitive advertising pressures varied these effects can be observed in the intent and usage rates. Finally shopping habits are needed to estimate the consumer's favored retailer so that distribution effects can be linked to preference and intent. Some of the questionnaires should be directed at finding out if people carry out their intent by recontacting some of the original respondents at a later time. Special awareness questionnaires are also useful in accessing interdependencies between brands.[28]

The panel of consumers in the test cities should be established and they should record at least the time of purchase, price, place of purchase, and receipt and use of samples. This data is a source for estimation of the trial rates in each period, the frequency of purchase, the repeat rates, and brand switching rates. It can also be used to access the effects of changing advertising levels on repeat rates if advertising varied over time or between cities. Finally it can be used in estimating the effects of samples in simulating trial experiences. It would also be useful to establish a continuing panel to record awareness to ads and appeals to estimate forgetting rate.

Salesmen's call reports supply the basis of estimating the success

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[28] See [37].

rate in stocking the product at retail and the ability of salesmen to

improve the instore display of the product.

Audits of media in the test cities are needed to determine the extent

of competitive advertising and serve as a check on planned advertising expenditures

by our firm. Internal company records supply data on advertising expenditures of

the firm and shipments of the product along with other data on planned strategies

and the bases for past decisions.

Test marketing data are necessary for the GO national decision, but

samples of the same type of data should be collected nationally if the product

is introduced, since the model is to be used adaptively during national introductio

These six items of data are necessary to support the model. They have

been described in only general terms, but a number of market research firms offer

such data collection services and a full discussion of such market research

methods is beyond the scope of this paper. The point should be stressed that

data at the behavioral process level can be collected and that it is the basis

of determining the model inputs. It is reasonable to estimate the costs of

collecting such information at about $50,000 - $75,000, but all this is not

incremental expense for the system since most firms collect most of this infor-

mation under current procedures.

THE STATISTICAL BANK

The burden of converting the raw data base information into model inputs

is the task of the statistical bank and the manager. This bank contains a

collection of multivariate statistical routines capable of exhausting the

information from a data base. To support the macro behavioral process model

presented in this paper, the statistical bank must contain at least the

following programs: (1) multivariate regression, (2) general conditional

classification and analysis program, and (3) non-linear estimation program.

The appropriate uses of these programs are presented in Table One along with
the data to be analyzed and the input to be produced.

Linear regression could be used in estimating the effects of instore
relative price effects in trial ($\overline{RPDIFT}$) by regressing the price difference
between the new product and its chief competitor's shelf price against the market share (or
sales) the new product achieved in the first periods of introduction in
similar size and types of stores. Lagged regressions could be used to
examine the effects of total advertising by all the products ($\overline{RADIND}$) by a
log-linear regression to total product group sales over time with an
appropriate carry over term.[29] These regressions lend insight into the
process assuming the usual pitfalls of regression are avoided.[30]

In analyzing the results from special awareness, preference, and
usage questionnaires it is useful to have a free format program that can
examine certain classifications of the data and calculate summary statistics
based upon them. An on-line program called Datanal[31] has been developed at
MIT to carry out this function. It allows sections of a data base to be
abstracted, analyzed, and cross tabulated with other sections of the data base.
For example, such a program could be used to analyze the special questionnaires
described in the data bank section. It could separate the number of people
who have used our product once and determine the specific awareness to ads or
product appeals. These appeal classes could be further analyzed to see how
many of each class have a first preference for our brand. Then the number
with first or second preference could be tabulated against their intent with
respect to future purchases. This capability is not only efficient, but it
allows the researcher to pursue each newly found insight to fully exploit the
information in the data base. This type of program could also be used to

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[29] See [26]; [30] See [32]; [31] See [23].

analyze consumer panel records to estimate the trial and repeat rates necessary in the model.

The final program in the statistical bank is a non-linear estimation program. This could be an iterative search routine that would minimize the variation between a set of observed data and a set of model generated data. The program could be best run as an on-line search where a market researcher specifies the initial values of the parameters and a set of increments to be evaluated.[32] This type of program could be used to estimate the sensitivities of price, facings, and special displays by minimizing the variation between observed sales in a store and the sales predicted by Equation (17).

Other statistical routines that are included in usual computer program libraries may also be useful in interpreting the data. In general the data base should be exhaustively analyzed so that all the insights it contains can be learned. For example, simple regressions of advertising to awareness and awareness to trial would be useful to conduct.[33] After all the statistical analysis is complete, the statistician and manager face the task of reviewing the estimates and generating the best set of inputs. He must review the data because the theoretical assumptions of all the statistical routines may not have been satisfied, the standard errors of the estimator may be large, or because alternate statistical techniques yielded different results. In addition the statistical programs only yield information about the statistical sampling error and he must interpret the data collection and measurement instrument bias. Finally some of the inputs may not be reflected in the data. For example, perhaps no data was available to evaluate the effects of alternate middleman deals on distribution. In this case he would have to make his best estimate of the response. He can, however, specify confidence intervals about his estimates and examine the sensitivity of the decision to the inputs by

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[32]See [39].

[33]See [11], [25].

running the model for alternate values.

The manager will remain a key element in the generation of input for new products because of the very complex multivariate and dynamic environment being analyzed and the rich base of prior knowledge the manager has accrued over his years of experience. An advantage of the behavioral process model is that it is structured in the way the manager visualizes the market. Successful marketing managers understand the behavioral processes of the market. Their experience can be linked to the process elements to gain the benefits of their good business judgment. In fact, the model's formal statement of the market processes usually leads to refinement of the manager's implicit model of the market and learning over time about the market mechanism.

INPUT-OUTPUT CAPABILITY

The manager should be able to easily communicate with the new product analysis system. He should be able to determine the sensitivity of the model to inputs so he can explore the full implications of alternate strategies, and to search for best strategies. This is best accomplished by a conversational on-line program which allows the manager to direct and interupt the system. The macro behavioral process model described in this paper has been placed on-line in a program called SPRINTER: Mod III. (See the appendix for a typical on-line session.) SPRINTER: Mod III allows the manager to access and display any of 300 of the model's inputs or calculated values by typing the command DISPLAY and an appropriate key number. He can display all data pertaining to the item or specific portions of vectors or matrices. In addition to the display capability, the manager can update any values from the console. The UPDATE command enables the managers to easily change input variables or parameters and by re-running the model can learn the sensitivity of the output to his changes.

A run of the model for some specified number of periods is initiated by the command GO. Another command is available to change model parameters. This is the modify capability. The MODIFY command allows the manager to change all or some values of a vector or matrix by multiplication of a constant that is specified on-line. All changes need not be made at the beginning of a run. The model can be stopped after some number of periods and, after changes in the model parameters, the RESUME command continues the remainder of the run with the correct value. The strongest command capability is SEARCH. The search command allows the manager to specify a number of alternate levels of each variable to be examined and the size of the step between each of the values. After the computer reports the estimated search time, the manager may initiate the search and the program finds the best alternative by examining all combinations of the values the manager asked to be examined. The manager can examine the detailed results of this search by the use of the DISPLAY command and can then continue the search over alternate ranges and smaller increments. The capability could be used to carry out factorial sensitivity testing.[34] The final command of the program is OUTPUT. This causes a copy of the stored values to be written out on a tape for later examination.

This type of conversational ability is satisfactory, but the state of the art is moving rapidly and it soon will be feasible to use graphical devices to display and update matrices and vectors. Graphical presentation is more meaningful to most managers and would enhance their willingness to use this model and their understanding of the system.

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[34] See [3].

APPLICATION AND TESTING

The model based information system proposed in this paper has been
applied to the analysis of a new frequently purchased consumer product
introduced by a medium sized firm. The firm had test marketed the product
in three cities and had collected all the information recommended for the
data bank except the test city consumer panel. They did, however, use very
detailed monthly questionnaires and it was possible to determine trial, repeat,
and frequency rates from these questionnaires by examining on a dissaggregate
basis the changes in usage reported each period. This application will be
described by reporting briefly (1) some examples of the insights gained from
the test data by use of the model, (2) the testing of the model for the test
market periods, (3) the use of the model in making the GO national decision,
(4) the accuracy of the model in predicting national market shares, and (5)
the adaptive use of the model in diagnosing and recommending solutions to
national introduction problems.

Interpreting Test Market Data

In deriving input for the model by applying the statistical procedures
outlined in the statistical bank section of this paper, several important
behavioral insights were gained. First, the use of Datanal to classify
buyers by purchase history revealed that the trial rate for the brand was
low (2% of the trial model population / month) and that the repeat rates
were high (60% in the preference model, 70% in the loyalty one model and 80%
in the loyalty two model.) The repeat rate indicates high user satisfaction
and a potentially strong brand if the trial rate can be established at a
profitable level. In addition, it was found that the trial rate was higher
in the first two months than in later months (3% in the first two months and

dropping to 1.5% by the fifth month.) This decreasing trial rate could be explained by the hypothesis that innovators are more trial prone, so as the innovators move through the trial model, the trial rate falls to levels of the majority of the consumers.[35] The realization of the diffusion process is important since it warns against over-optimism due to high initial sales.

To determine the in store effects of price on trial ($\overline{\text{RPDIFT}}$, Equation 9), disaggregated store data in the three cities for the first three periods were used. Regressions of market share of the new product against the price difference between the new product and the standard price of the older competitive product in each store were carried out. The regressions were significant at the 1% level as were the t statistics for the coefficients. The single best expression for $\overline{\text{RPDIFT}}$ obtained from the regressions and managerial judgment was:

$$\overline{\text{RPDIFT}} = 1.3 - 1.5 \; ((PR_1 - SPR) \, / \, SPR)$$

PR   =   price of product by our firm

SPR   =   standard price of old product

This implies that at higher price differentials fewer people exercise their intent. This is as economic theory would suggest, but there had been the belief in the company that consumers were judging the quality of the product by its price and therefore a premium price had been established for the product. If this had been so, the higher prices would not have reduced the trial rate. The regression coeficient was confirmed by regressions in each individual city, store type, and period.

The effects of advertising were obtained from regressions of sales versus advertising levels between cities and over time. Six alternate multivariate lagged models were run and one to five percent significance was found for the advertising elasticities. The carryover effects were small and not significant, apparently because of the rapid forgetting rate

[35] See [29] for related findings for other products.

of consumers for this type of advertising. A managerial review of the regression values indicated that the best estimate of the elasticity of advertising was +.3 .

These three examples of the specific input analysis supply the reader with a feeling for the general input generation approach. The data was exhausted for information and managerial judgment was used to interpret the results and obtain the best model input. This was a very time consuming process and required extremely close cooperation between a statistician, market researcher, brand manager, and model builder. In addition to the best estimate, confidence intervals were prescribed so the uncertainty about the sales forecast could be imputed to the risk associated with the product.

In this application it was found that the model fostered a systematic review of the test data and a more objective and analytical examination of the diffusion process than had been undertaken under existing procedures. The new insights gained from the generation process were also found to be useful to the brand managers in sharpening their understanding of the market procedures underlying new frequently purchased consumer goods.
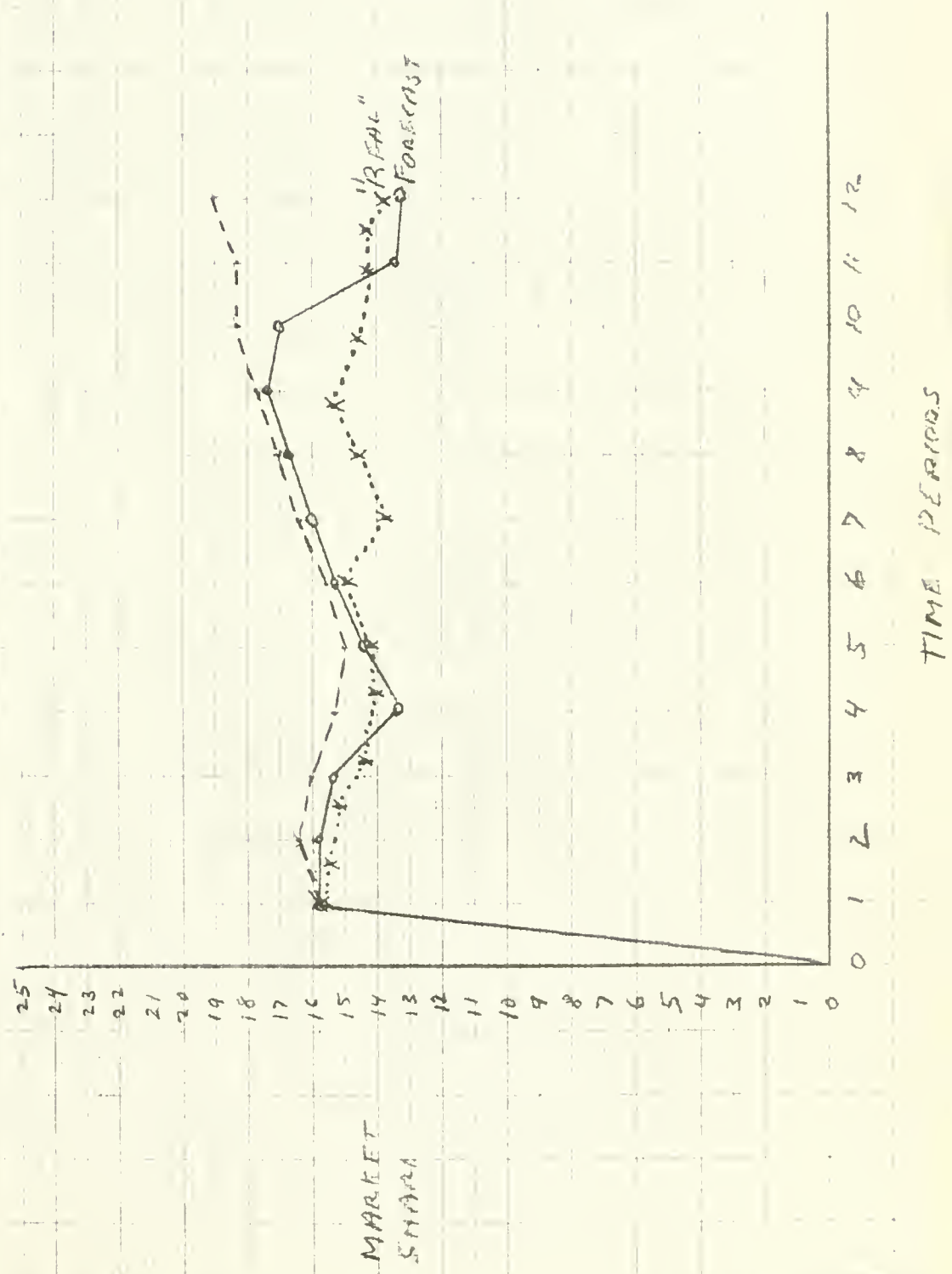
Model Accuracy in Duplicating Test Market Shares

If the input had been accurately obtained and the model structure is valid, the model should have been reasonably accurate in duplicating the market shares that were observed for the brand in test market. The model generates the market share given the behavioral process input and the firm's and its competitor's controllable variables. In this test market, as in many consumer product tests, the competitor attempted to confuse the test market results by doubling his advertising and sampling 25% of the market with a regular size container of his product. Figure Four shows the test market share predictions if the test had accurately depicted the planned national strategy.

The share started high, but decreased as the innovators moved out of the trial model, then a steady growth was predicted due to the high repeat rate and stabilization of the trial rate. Figure Two also shows the prediction when the competitor doubled his test city advertising in periods two, three, and four and sampled heavily in period two. The decrease in shares in periods 10, 11, and 12 was due to our phasing out of advertising and the completion of test marketing. The real market shares in Figure Two are based on the market shares in the samples of audited stores in the cities. The test forecast with competitive interference matches closely the real market shares, particularly in the first six months. In the later periods there is a spreading between the real and predicted share. This is due to a failure of the model to predict the down turn in period seven. There was no explanation available for this down turn, but perhaps some competitive action had occurred that was not observed or the non-random sample of audited stores was subject to a bias. It is encouraging, however, that the slope of the real and predicted shares are similar after the dip in the real share.

The match between the predicted and real shares were deemed reasonable by management given the input accuracy and the measurement procedures for "real" market share. The test market testing of the model indicated that it was valid in terms of the accuracy demanded by management.

FIGURE FOUR

MODEL TESTING: TEST MARKET DATA

- - - = FORECAST WITH NO COMPETITIVE INTERFEREN'

——— = FORECAST WITH INTRA-FORECAST FROM COMPETITOR AND PHASEOUT

······ = OBSERVED MARKET SHARE

"REAL" FORECAST

FORECAST

MARKET SHARE

TIME PERIODS

The GO National Decision

The decision to introduce the product should be made on the basis of the differential profit it will generate for the firm compared to its risk and investment in the product. This requires a forecast of national market share and sales. The behavioral process model can generate this forecast on the basis of the test market estimates of the model's parameters adjusted for any differences that may be expected between the test and national responses. Usually some adjustments are necessary since the test cities are usually small or medium sized cities like Syracuse, New York or Peoria, Illinois, which are not representative of the national response to the product. For example, distribution is almost always above the national level for each month after introduction. In addition, the advertising response is usually overstated since the usual translation of a national campaign overstates the relative competitive advertising pressure. Furthermore, people in these cities may not respond in the same way as New York city residents who have developed more callousness to advertising. In this application management made the following adjustments to reflect differences between test and national behavioral response: (1) trial rates for each awareness class were reduced 10%, (2) the effectiveness of advertising in creating awareness was reduced 10%, (3) the proportion of people who convert intent into action was reduced 10%, (4) the initial levels of distribution were lowered to reflect expected national levels of availability at introduction, and (5) the starting point of the campaign was delayed because national plans called for a later time of introduction than in test.

Under these conditions and the existing national plan, the forecast of national sales indicated a cash flow contribution to the firm of $1,130,000 in the first three years. Discounted at the firm's target rate of return of 40%

per year yielded a present value of $414,000. When this discounted differential profit was compared to the initial investment of $300,000 and the uncertainties of estimation, there was a 51% chance of achieving the target rate of return on investment in three years. This was not sufficient to justify a GO decision. But these existing reference plans did not reflect the best strategy for the brand. Utilizing the SEARCH option of the program and examining over 100 strategies it was found that 15% lower prices increased the discounted profits to $706,000. The advertising level specified in the reference plan was found to be at the best level when lower prices were utilized. The iterative search produced a strategy that represented a 70% increase in profits. The lower prices specified in the "best" strategy reduced the number of people who would not exercise their intent to try (see Equation 9) and increased the instore effectiveness as visualized by preference and loyalty buyers (see Equations 17 and 18). Even at the higher profits, however, there was only a 54% chance of achieving 40% ROI in three years.

This initial test of the new product information system was carried out after the product had been in national marketing for eight months. The GO decision had been reached on the basis of subjective forecasts of a market share growth rate which was considerably more optimistic than the model's prediction. The product was introduced at the planned premium prices, so the recommended strategy and profit increase have not been tested and the profit increase must be termed a predicted increase. The model would not have recommended a GO decision at the old planned levels and even with a better strategy would not have recommended introduction since the probability of returning the target rate of return was below the firm's GO criterion of 65%. A 65% probability of achieving the ROI objective could be achieved if a much better advertising

appeal could be found. It would have to create 25% better awareness for the same dollar expenditures and a 25% higher trial rate for people with specific appeal recall. If a campaign of this quality could be devised, the appropriate advertising budget would be the same level as for the old campaign. The use of the search option indicated that decreasing the budget ten percent would reduce profits seven percent, that increasing the ₐbudget ten percent would reduce the profits one percent, and that increasing the budget by twenty percent would reduce the profit 2.5 percent.

In summary, the model indicated that: (1) it would not be appropriate to introduce the product at the reference strategy, (2) 70% more discounted differential profit could be obtained from a better strategy, and (3) even at the better strategy the product should not be introduced. The model, using only test data, would have recommended that the product be improved before introduction and indicated that a better advertising appeal could generate the needed improvement.

National Introduction Testing and Model Forecasting Accuracy

Since the product used for testing the model had already been introduced nationally, the forecasting of the model and its problem finding capabilities could be tested even though at the firm's strategy the model could not have recommended a GO decision. The same data collected in test market was collected during national introduction on a sampling basis. This enabled the behavioral process parameters to be monitored during early introduction.

Within a few weeks of introduction, feedback from salesmen indicated the product was "not moving." The causes of this problem were found by examining the results of the national awareness and usage questionnaires carried out four weeks after introduction. These surveys showed that the awareness rates were

down 20% from the predicted value and that the trial rates for those who were aware were 10% below expectation. The source of the reduction of the conditional trial rate was that the innovators nationally were not responding as rapidly as in the test cities. The 20% reduction in awareness in part was due to an error in translating the national advertising budget to the test market cities. Too much advertising was inserted and the observed test levels were therefore artificially high.[36] The remaining reduction seems to have been due to a low national response to the advertising. The firm responded to this information by doubling advertising.

At the beginning of the third month of national introduction the major competitive firm unexpectedly introduced a brand to directly compete with our firm's new product. They backed this introduction with a 50% increase in their advertising level. This new product advertising lowered our trial rates (see Equation 6) and reduced the proportion of people in the preference model who translated preference to intent to repurchase (see Equations 15 and 16). These effects were monitored in the second national awareness survey. This survey was carried out ten weeks after introduction.

This three city awareness survey also indicated some behavioral changes in addition to the effects of the competitor's new product. In particular, based on a comparison of the responses levels in the cities, it was found that the awareness response function had shifted back to the level specified prior to introduction. The trial rates for the specific awareness classes also returned to their expected levels. This recovery was apparently due to the innovators being held out of

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[36] It is moot point whether the use of the information system would have found this error before the GO national decision was found. It is the author's opinion that in generating the input for the model, the examination of the relative dollar expenditures would have resulted in a good chance (greater than 75%) of finding the translation error.

the market by the initially low awareness levels and entering later than expected. The slow start of the product caused the innovators to spill over into the first five months rather than just the first three months as had been observed in the test cities.

Six months after introduction media audits showed the competitor had become very aggressive and had doubled his advertising relative to expectations. This new competitive rate was nearly equal to the total industry advertising in the previous year. The firm responded to this competitive activity with a continued high level of advertising in periods 5, 6, and 7, but had to reduce spending in periods 8, 9, and 10 since they had depleted the product's advertising budget. In periods 8, 9, and 10 the competitor also reduced his rates of advertising to his previous level.

The accuracy of the model in duplicating the actual national introduction market shares is shown in Figure 5. The real market shares are based on Nielsen store audits and the model predictions are based on the prior test market estimates updated for the changes in national environment described in the previous paragraphs. The model seems to be very accurate in its updated forecasts. These forecasts were made in the ninth month after introduction, but before the Nielsen market share for months eight and nine were available. The model predicted a down turn in the share for months seven, eight, and nine. Subsequently, the Nielsen market share report showed this to be accurate not only to the extent of predicting the turn, but also the amount of the drop. It should also be pointed out that the model was much better than management's existing procedures which were in error by over 100%. Model testing also was carried out at the micro level. For example, the growth of availability predicted by the model closely matched the Nielsen measurement of availability. The testing of the model on the national data indicated the model to be valid in terms of management's standards of the accuracy required in a new product decision model.

FIGURE "FIVE"

MODEL TESTING: NATIONAL INTRODUCTION DATA

———— = MODEL PREDICTIONS

– – – – = OBSERVED NIELSEN
MARKET SHARE

MARKET
SHARE
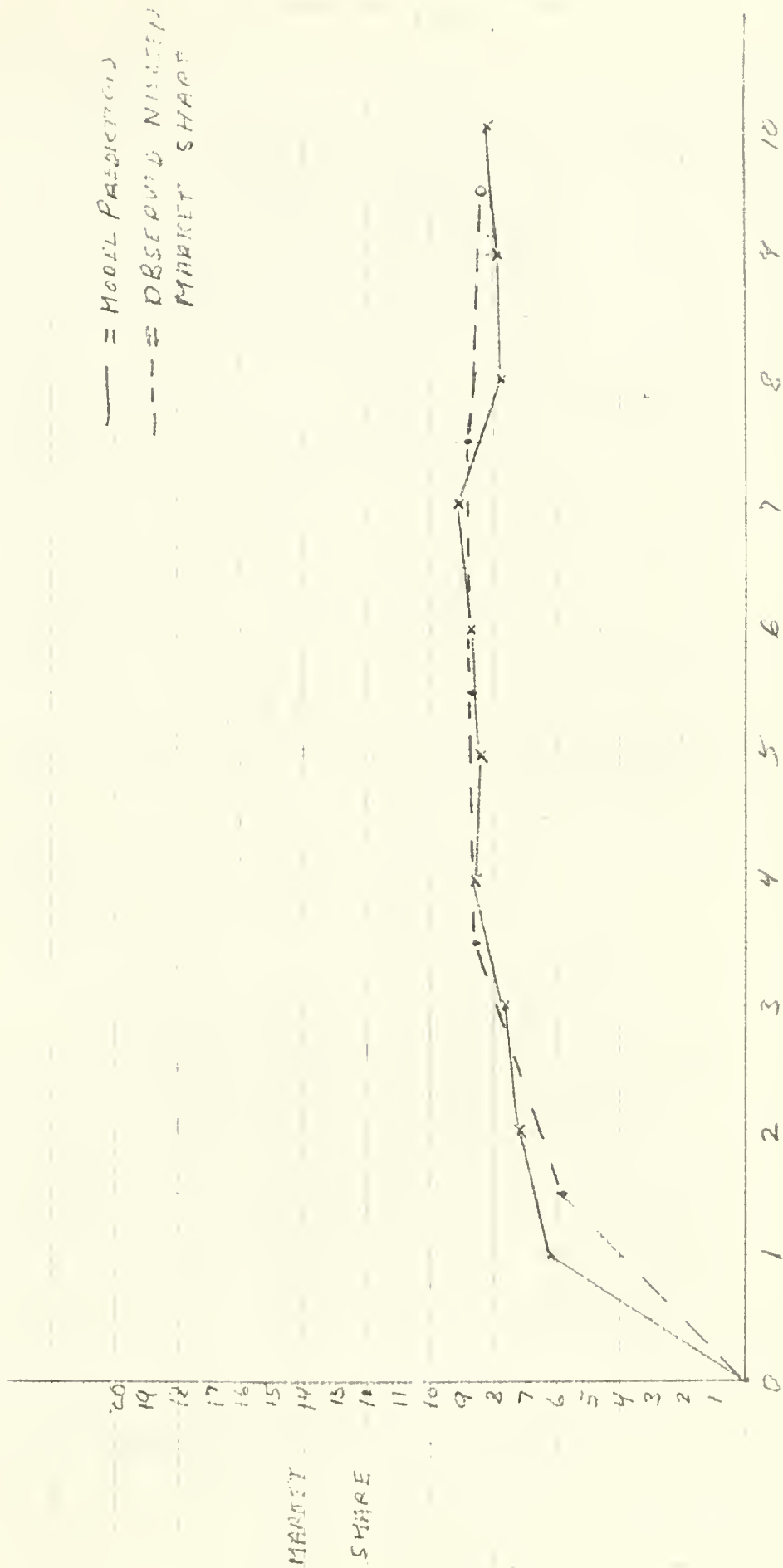
TIME PERIODS

After testing on the basis of national data, the model served to analyze the decision to drop or to continue the brand. The model showed that if the price level were reduced as originally recommended and if a new 40% better advertising campaign could be mounted, the brand would respond and achieve 19% market share and return two million dollars in cash flow profit in three years. These are essentially the same changes that the model would have originally required for a GO decision, and it is reasonable to say that the model could have saved the firm a year of painful and highly unprofitable national experience.

Adaptive Use of The Model During National Introduction

During national introduction the model can serve as an adaptive mechanism. In this application the data bank developed on the basis of national experience was used to update the model's parameters and search for a best response to the new information.

The first new information was contained in the first month's national awareness questionnaires and indicated that the advertising response function was lower than expected and that the trial rates were below expectation. The SEARCH capability of the model was utilized to examine alternate advertising
(15% lower than reference)
levels assuming the best price had been established for the product. It indicated that the best advertising strategy was to hold to the original plan. In contrast, the firm actually doubled advertising. The model indicated this would reduce profit by more than $200,000.

The second set of new information was monitored in period three. It indicated that the competitor had introduced a new brand and backed it by 50% increase in advertising. At this same time the second national awareness questionnaire indicated trial rates and the advertising response function had

recovered to their expected levels. As mentioned previously this was diagnosed as the late arrival of the innovators and so the period 3, 4, 5, and 6 trial rates were raised 10% from their reference values to reflect the spill-over of innovators into later periods. The search capability was again used and an increase of 20% in advertising and a 10% reduction in price were found to be the best responses to the increased competitive activity and the basic behavioral response changes. The remainder of the adaptive testing was based on these changes having been implemented in period 4. The price change could have been implemented by a price-off deal.

In period 6 the national media audits indicated that the competitor had doubled his advertising expenditure. Since it was felt that this was a short-run strategy change the model was updated by increasing the competitive expenditures only in periods 6, 7, and 8. The best response to this aggressive competitiv action was to hold to the previously recommended level (20% more than reference.)

In period 8 the media audits reflected the competitor's return to the previous level (50% greater than reference) and the best response to this was to reduce our advertising 20%. This decrease was implemented in period 9.

The adaptive testing procedure for the first ten periods and the projected results, based on the assumption that the period 9 strategy was used until period 36, generated a cash flow profit of two million dollars. The company's actual strategy of higher prices and its non-model adaptive strategy would have generated only $500,000, so the combination of the better introductory plan and the national adaptive strategy determination generated an estimated additional $1,500,000 of cash flow profit. Since the GO national lower price strategy was estimated to add $600,000 of cash flow profit, it appears that the use of the adaptive capabilities of the model is at least rewarding in terms of profit improvement as the GO national decision search capability.

SUMMARY

This paper represents an attempt to integrate behavioral theory within

a normative mathematical model for use in the analysis of frequently purchased

consumer goods. The macro behavioral process model reflected the consumer

decision process of starting at awareness, continuing to intent, search, choice,

and ending in word of mouth generation and forgetting. This process was described

in five depths of class models: trial, preference, loyalty I, non-loyal, and, loyalty

In each model the effects of the controllable parameters of the firm were

emphasized so the model would have the power to recommend. Advertising creates

a compatability of the innovation to the buyer and an awareness of the felt

needs it might fulfill. The distribution of samples are an attempt to show how

the product fulfills needs and bestows benefits. Price is a factor in the

relative advantage of the product while sales effort affects the availability

of the product to potential adoptors. The formal mathematical statements of

these phenomena represent a set of hypotheses of how the market operates.

The use of the model over time will allow data to be collected which can vali-

date the market mechanism. This understanding and learning about the market

and its acceptance mechanisms are the keys to successful new product analysis.

The macro behavioral process model was positioned within an information

system consisting of the model, a data bank, statistical bank, and input/output

capability. The contents of the model's behavioral input requirements led to

a specification of the data bank and statistical bank. This specification

fosters an efficient use of data because consideration of the disaggregated raw

data is necessary in generating the response parameters. These statistical

estimates when combined with managerial judgment represent the model's input.

The model was placed in an on-line conversational program called SPRINTER: Mod III

which allows a manager to DISPLAY, UPDATE and MODIFY the data. He can also initiate a man-machine heuristic SEARCH for the best strategy alternatives and thereby utilize the normative power of the system.

The outputs of the model are: (1) behavioral insights into the test market product environment, (2) a specification of the best strategy and its profit and risk implications, (3) a recommendation of GO, ON, or NO for the product, (4) an adaptive capability to diagnose national introduction problems, generate updated forecasts, and recommend strategy responses to the national changes. Initial testing of the model indicates that it can accomplish these objectives and substantially improve profits and that the model is reasonably accurate in forecasting market shares for a new frequently purchased consumer product.

After an initial model development and programming cost of $200,000, the cost of applying this model on a continuing basis is estimated at $25,000 per product in addition to the data collection costs. This model is being made available to multiple users on a time-sharing basis so the fixed cost for any company would be small. The variable cost represents about 30-50% increase above the usual costs of test marketing, assuming the information required for the data bank is already being collected. This cost seems reasonable when compared to the potential to increase profits demonstrated in the example (greater than 50%) and the possibility of preventing multimillion dollar new product mistakes. The continued use of the proposed model based information system should lead to improved profits and a reduction in the new product failure rate through a better understanding of the market's structure and behavioral response process. as well as a better strategy determination and a better GO, ON, or NO decision.

APPENDIX

Hypothetical On-line Computer

Session with SPRINTER: Mod III

✓ = data typed by manager; all other data is model output.

[ ] = comments about program to guide in interpretation.

RESUME SPRINTER

EXECUTION.
*
/INPUT...USE NATIONAL FORECAST DATA BANK   [Request to input test market
 GIVE INPUT TAPE NUMBER   data stored on tape 66]
/66

                                                           [Forecast national environ-
*   ment on basis of test data]
/GO...RUN 36 MONTHS
 TDDPRF = .523E 06,FSSP = 8,P(TGT-QBK)=.49844,P(PGT-RR)=.51032 [TDDPRF = total discounted
                                                                    differential profit]
*   ┌FSSP = first self sustaining period]
/DISPLAY MARKET SHARE BY MONTH   │P(TGT-QBK) = probability of achieving target payback]
/273   │P(PGT-RR) = probability of achieving ROI objective]
 MONTH   └
+
/0   [273 is the code number for market
                                                            share, "0" indicates all periods]

                       MONTH
      1   2   3   4   5   6   7
      8   9   10   11   12   13   14
     15   16   17   18   19   20   21
     22   23   24   25   26   27   28
     29   30   31   32   33   34   35
     36

  1   .455E-01   .564E-01   .575E-01   .509E-01   .482E-01   .518E-01   .560E-01
      .605E-01   .661E-01   .682E-01   .693E-01   .739E-01   .727E-01   .789E-01
      .880E-01   .894E-01   .932E-01   .940E-01   .954E-01   .952E-01   .102E 00
      .105E 00   .956E-01   .998E-01   .895E-01   .950E-01   .106E 00   .107E 00
      .112E 00   .114E 00   .116E 00   .119E 00   .126E 00   .128E 00   .123E 00
      .127E 00

+

MODIFY   --   REDUCE OUR SUGGESTED RETAIL PRICE BY 10%
 140
COMPETITOR
+
 1
 =
 .90   [Simulation of lower price -
                                                            MODIFY command multiplies old
                                                            value by specified constant
                                                            (.90 in this case)]
*
/GO SIMULATE LOWER PRICES FOR 36 PERIODS
 TDDPRF = .758E 06,FSSP = 8,P(TGT-PBK)=.51985,P(PGT-RR)=.54927

*

UPDATE...ADD SAMPLING OF 750,000 IN EACH OF FIRST THREE MONTHS
132
MONTH
+
-1   [-1 indicates a range of months is desired]
FIRST MONTH
1
LAST MONTH
3
COMPETITOR
+
1
=
750000.

*
DISPLAY SAMPLING OF OUR FIRM
132.
MONTH
+
-1
FIRST MONTH   [Display of samples to see update is as desire
-1
LAST MONTH
-5
COMPETITOR
+   [Competitor 1 is our firm]
1

COMPETITOR   MONTH
          1   2   3   4   5

   1   .750E 06 .750E 06 .750E 06 .000E 00 .000E 00

*
GO...RUN 36 MONTHS
TDDPRF =   .367E 06,FSSP =   8,P(TGT-PBK)=.48767,P(PGT-RR)=.50700

*
DISPLAY SAMPLE USAGE RATE
23
MONTH
+
1   [Preparation for sensitivity test of differ-
                                             ent usage rate and sample cost]
SEGMENT   MONTH

   1   .330E 00

*

[Adding samples by updating sampling variable to desired level]

U SET FOR SINGLE MONTH RUN
 4
 =
 1

*
GO...RUN ONLY FIRST MONTH
MO S   TTBUY   IPBUY   TLBUY   NIND   NTRIAL   NPREF   NLOYAL
 1 1 .240E 06 .000E 00 .000E 00 .170E 08 .167E 08 .000E 00 .000E 00

*
DISPLAY # AD OR APPEAL AWARE IN TRAIL MODEL AFTER ADV EXPOSURES
 157

[These displays show depth of deta
                  in retrieving behavioral data.]

                         SEGMENT

   1   .403E 07

*
DISPLAY # WITH INTENT TO TRY OUR BRAND IN FIRST MONTH
 159

                         SEGMENT

   1   .273E 05

*
DISPLAY # WITH INTENT TO TRY OUR BRAND IN FIRST MONTH (BY AWARENESS CLS)
 158
AWARENESS CL
 +
 0

SEGMENT   AWARENESS CL
         1   2   3   4   5   6   7
         8

   1   .000E 00 .220E 05 .297E 06 .424 06 .131E 06 .000E 00 .000E 00
       .000E 00

*

DISPLAY # WHO HAD INTENT TO TRY OUR BRAND AND WHO FOUND IT IN A STORE
152
STORE TYPE
+
0

	STORE TYPE		
	1	2	3
1	.283E 06	.657E 05	.668E 05

*
DISPLAY # WHO ACTUALLY BOUGHT OUR BRAND DURING FIRST MONTH BY STORE TYPE
235
STORE TYPE
+
0

SEGMENT		STORE TYPE	
	1	2	3
1	.163E 06	.379E 05	.383E 05

*
DISPLAY # IN AWARENESS CLASSES OF TRIAL MODEL AFTER FORGETTING
257
AWARENESS CL
+
0

SEGMENT			AWARENESS CL				
	1	2	3	4	5	6	7
	8						
1	.151E 08	.942E 06	.227E 06	.249E 06	.216E 05	.136E 06	.464E 05
	.000E 00						

*

```
*
√SEARCH...TEST VARIOUS PRICE, ADVERTISING MIXES FOR MAX. PROFIT
```

VARIABLES ARE   ⌈Search all combinations of three
(AD,PR,SM,CP,DL,SC)   │levels of Price and three of Ad-
                                         │vertising and report best results⌋

```
WSSS.DDD
√PR  3 .10              THREE STEPS OF 10%
√AD  3 .20              ADV ALSO THREE STEPS, BUT 20%


√F OF COMBS=            9
 ESTIMATED EXECUTION TIME=     45.00 SECONDS

TYPE 'GO' TO COMMENCE SEARCH,ELSE PUSH RETURN


√GO...COMMENCE SEARCH
   ADV      PRICE     SAMPLES   COUPONS   DEAL      CALLS    TDD PROFIT
   .80000    .90000   1.00000   1.00000   1.00000   1.00000     530801.38
   .80000   1.00000   1.00000   1.00000   1.00000   1.00000     320349.71
   .80000   1.10000   1.00000   1.00000   1.00000   1.00000     -98837.94
  1.00000    .90000   1.00000   1.00000   1.00000   1.00000     757512.13
  1.00000   1.00000   1.00000   1.00000   1.00000   1.00000     505272.05
  1.00000   1.10000   1.00000   1.00000   1.00000   1.00000      -8219.40
  1.20000    .90000   1.00000   1.00000   1.00000   1.00000     558293.65
  1.20000   1.00000   1.00000   1.00000   1.00000   1.00000     294876.81
  1.20000   1.10000   1.00000   1.00000   1.00000   1.00000    -260795.16

BEST RATIOS ARE
  1.00000    .90000   1.00000   1.00000   1.00000   1.00000     757512.13

*

 OUTPUT THIS SESSION FOR FUTURE USE
 GIVE INPUT TAPE NUMBER FOR NEXT SESSION
 57
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